A parametric study of segmentation thresholds for X-ray CT porosity characterisation in composite materials

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Abstract

Porosity in composites is a critical manufacturing defect that leads to a reduction of mechanical performance. Non-destructive testing (NDT) techniques are used to inspect composites after manufacture to identify defects and to help assess their impact on mechanical performance. Micro X-ray computed tomography is a promising NDT technique which provides information about pore location, size and morphology. To identify and characterise voids, an image 'segmentation' must be applied to the full CT dataset, which is simply a rule-based decision about whether a voxel is inside a pore or not. This work uses a simple model to analyse and compare the effectiveness of previously accepted threshold methods for segmentation across a range of material and porosity parameters. A new CT-segmentation thresholding method is proposed and evaluated for characterising voids in a wider range of composites. The sources of uncertainties are investigated and recommendations are made to minimise these uncertainties.

Keywords: A. Polymer-Matrix Composites (PMCs), B. Defects, D. Non-destructive Testing

1. Introduction

Porosity in composite structures is one of the critical manufacturing defects because it leads to a reduction of mechanical performance of the structures, particularly the interlaminar shear strength [1]. It is almost impossible to eliminate it during manufacturing, especially if non-autoclave techniques are used. Most of the relevant published research has been focused on correlation of the average through-thickness void volume fraction to the mechanical properties, whilst the individual void features and their distribution have now been shown to be potentially more important in the failure analysis. [2] shows that the position of the voids through the thickness of the composite, and the effective radius of the largest void, provide better correlation to interlaminar shear strength than just the average void content. For this reason, in order to perform research into the effect of porosity defects on strength it is important to determine the distribution, size and morphology of the voids in a component, non-destructively.

Non-destructive testing (NDT) techniques are used to inspect composite structures after manufacture to remove the possibility of unacceptable defects. The most common non-destructive method to check for porosity in composites is ultrasound through-thickness attenuation measurements [1,3,4]. The measured ultrasonic attenuation can be correlated with through-thickness average void volume fraction but the correlation is poor due to the dependencies of attenuation on the other porosity parameters such as pore size and distribution. Whilst ultrasonic attenuation is sensitive to void volume fraction, size distribution and depth distribution, standard through-thickness attenuation measurements cannot differentiate between these. The result is that the uncertainties in the quantification of bulk porosity are large, making it very difficult to reliably achieve the desired low levels of porosity in production. For example, if 2% void volume fraction, V_v is the maximum allowable and the 95% single-sided confidence limit in the measurement is 1.2%, then the measured V_v must be less than 0.8% to give the required 5% probability that the actual porosity V_v is greater than 2%.

Frequency dependence of ultrasonic attenuation does give a handle on size distribution but this has not been used successfully for porosity in an inhomogeneous anisotropic solid [5]. Recent attempts to decompose the frequency-dependent pulse-echo response into separate contributions from porosity and thickening of resin layers by [6], and [7], [8] have had some success in producing a 3D map of local porosity. Whilst these methods have shown potential, they still need further work to improve the decomposition process.

Other NDT methods such as thermography and use of microwaves could be applicable in porosity determination but with some difficulties in practical use. Due to the resolution of these methods, they will only respond to volume-average void content, rather than providing the information about the location, size and morphology of each void that is needed in this study. [9–12].

Acid digestion is an alternative technique that is able to give an estimate of the void content in a specimen [13],[14], although the technique is destructive, does not provide details of void morphology and has uncertainties that are generally larger than required for validation of NDT methods. Reliable information regarding void morphology and distribution can be determined by optical microscopy [15,16], [14], [17];

however, this technique is restricted to 2D and requires samples to be cut in multiple sections, which leads to a loss of some information, and of the sample itself.

Micro X-ray computed tomography (CT) is a promising non-destructive technique, which can give information about pore location, size and shape in three dimensions [17–22],[23–25]. However, the technique is only able to accommodate small sample sizes, so that a high-resolution image of the individual pores can be obtained. Usually, validation of the CT images is performed by comparison with optical microscopy of slices of the sample, which give high-fidelity measurements of the individual voids captured during CT-imaging.

After CT-scan reconstruction, the object is represented as a set of voxels. Each voxel has a grey level, which is directly related to the effective linear attenuation coefficient (LAC) for X-rays of the incident photon-energy distribution in the corresponding voxel of the specimen. If the voxel contains more than one material, such as the edge of a pore and some composite, the effective LAC is comprised of a simple volume-weighted combination of the LACs of the constituent materials [26] – the 'simple volumetric mixture rule' – which is really important for the work in this paper. The value stored at each CT voxel is called the grey level and is related to the effective LAC via contrast (gain) and brightness (offset) controls [27] and a transfer function that is primarily linear but, unfortunately, can vary slightly within the scan due to complications such as beam hardening. For the purposes of this paper, a constant, linear transfer function will be assumed. The grey-level histogram of the sample generally has two peaks, which represent air and composite material; sometimes, if there are thick resin layers or other resin-rich regions, it is possible to detect three peaks, which correspond to air, resin-only and composite. However, in most of the cases, the resin-only and composite peaks are merged due to similarities in their attenuation coefficients and the width of their scattering-noise distributions. To identify and characterise the morphology of voids in the specimen, an image 'segmentation' must be applied, which is simply a rule-based decision about whether a given voxel is inside a pore or not. Thus, image segmentation assigns voxels to one of the groups: 'air' or 'material'. There are two thresholding methods that can be applied for image segmentation – global and local thresholding. The simplest tool is to use a global threshold to separate these voxels: below the threshold is 'air', above the threshold is 'material'. A local threshold is a varying threshold that can be determined by splitting the image into sub-images and calculating the threshold for each sub-image, or by evaluating the image intensities in the neighbourhood of each pixel

[28]. Generally, local thresholding methods are more time consuming and computationally expensive in comparison to global thresholding methods. Moreover, most of the commonly used CT-processing software packages only allow the use of global thresholds. Although the advantages of using a local threshold over a global threshold, have been shown in a number of studies [29–31], these studies compared the thresholding methods without actually knowing the 'true' value of the compared parameters. It is therefore difficult to state, with certainty, the relative accuracy of each thresholding method.

A segmentation threshold can be manually selected [32], however its selection relies heavily on user interpretation. This introduces uncertainty to the results, as the results can be highly sensitive to changes of the threshold, particularly when the pore size is small so that there is a high ratio of pore-edge voxels, including part of the edge of a pore, to internal pore voxels. Researchers have suggested improvements to manual threshold selection in which a reference sample is CT-scanned at high resolution, so that a threshold is manually determined based on high resolution scans and then subsequently used for the remaining lower resolution specimens [33,34]. Optical microscopy has similarly been utilised for calibration of the chosen threshold [24], however these techniques are flawed for morphology characterisation because they will affect each pore size and shape differently.

Other works have used the 'Otsu threshold' of minimization of variance between the material and air voxel populations [35], which is basically a first-moment method to segment the histogram, analogous to a centre-of-mass calculation. Some researchers based their threshold on a local variance method from Niblack, adapting the threshold according to the mean and standard deviation of the higher-attenuation peak, belonging to the composite material in this case [36]. Others used algorithms embedded in image processing software, such as Avizo [37], Fiji™[25], ScanIP [23]. Kastner et al. [18] did a comparison of the effect of different thresholds on the porosity measurement by comparison with acid digestion. However, the void content determined from acid digestion is known to vary depending on factors such as the amount of acid used, the digestion time, and the temperature during digestion. Experimental errors are also introduced by the accuracy of the weight measurement scales, and accuracy of the physical densities of the fibre and resin used in the calculations [38].

Plank et al. [39] used reference samples with artificial porosity created by drilling holes in order to assess and compare different thresholding methods. The void content of the reference samples was determined by taking an average of the measured diameters of the holes, calculated manually from high-resolution microscopy images assuming an ideal cylindrically shaped hole. However, an average value is required in order to tackle the inherent inaccuracies of the method. For instance, the drill is unlikely to be perfectly perpendicular to the composite surface during drilling, and the drilling itself is liable to introduce delamination, fibre splitting, and breakout of the back surface of the laminate, which are difficult to observe and impossible to account for with this method. More recent work by Plank et al [40] used high-resolution Micro-CT scans to determine the true porosity and then showed that the required threshold to give the true average V_v increased with increasing voxel size.

Nikishkov et al. [20] also used samples with porosity created by drilling holes. The manufactured samples were used to compare different thresholding techniques and, in particular, to validate a proposed density-based contouring method, which is based on the assumption that CT grey values are proportional to material density. The method uses sub-pixel contour generation for the average of the air and material grey values obtained in CT scans. The results showed that a threshold at 0.5 (on a normalised grey scale where the air peak is at zero and the composite peak is at 1) is the most accurate thresholding method of those investigated (other thresholding techniques including minimum threshold, Fuzzy C-means threshold, sub pixel edge detection). Although the authors showed that the threshold at 0.5 for pore detection works well, they did not compare the measured void content with the true value or conduct a parametric study of bias in the measurements, as this could not be achieved experimentally. In fact, the predilection of comparisons to experimentally produced reference samples have meant that no works have investigated the effects of different X-ray, sample or porosity parameters on porosity characterisation.

The current paper uses a simple model to investigate the effects of different segmentation thresholds, based on simple volumetric mixture rules applied to the composite and void content of each voxel in the structure. Whilst significant work has been reported on the modelling of X-ray generation [41–43], attenuation by materials [44,45], and the simulation of voids in the X-ray CT process[46,47], these models are much more complicated than is required for explaining many of the effects of different segmentation thresholds in terms of void size, volume fraction and morphology. The kind of model used below has not been reported for X-ray CT segmentation studies but has been used for investigations of defect sizing from ultrasound C-scan data [48].

The objectives of this paper are to propose a simple, rigorous, reproducible and accurate CT-segmentation thresholding method to characterise voids in composites, to study the sources of uncertainties in the results using modelling and simulation, and to recommend methods to minimise those uncertainties. In section 2, the segmentation method is described and justified based on the physics and known properties of X-ray CT imaging methods. The model used for simulation of the multi-dimensional parameter study is described in section 3, followed by some modelling results and validation by comparison with experiment in section 4. A parametric study of the segmentation thresholds is reported in section 5 and improvement of the threshold in the special cases is described in section 6.

For the rest of this paper, a 'normalised grey level' scale will be used where the grey level of air is set to zero and the grey level corresponding to the 'nominal' fibre-volume fraction (V_f) of composite is set to unity. Grey level varies with V_f, which is not uniform in the composite, but this is treated as one of the parameters in the parametric study later.

2. Proposed segmentation method.

The segmentation method has to determine whether a given voxel is to be counted as inside a pore or not, based purely on its grey level. Grey level is assumed to be linearly related to the effective LAC in the voxel, which is a combination of the LACs of the voxel's component materials for the relevant photon-energy distribution [49]. These materials contribute to the effective LAC using a simple volume-weighted mixture rule, which means that the threshold on grey level is effectively a threshold on the relative volumes of air and composite in the voxel, neglecting any variations in the transfer function due to changes in the photon-energy distribution across the scan volume. Obviously, the critical voxels for measuring pores are the ones that straddled the edge of a pore, containing some air and some composite, and the segmentation threshold has to apportion these in a way to minimise any bias in the resulting pore measurements, including the full-volume void volume fraction, V_v.

The basic assumption in the proposed thresholding method is that a voxel should count as a pore-voxel if more than half of its volume is air, otherwise it is not counted as being in a pore. Obviously, the contentious voxels will be the pore-edge voxels that are intersected by the edge of a pore. The statistical reasoning behind the assumption is that the errors in apportioning pore-edge voxels as air should be fully compensated by the errors in apportioning pore-edge voxels as composite. This is shown in Figure 1, in which the histogram displays a roughly constant count of pore-edge voxels (between grey levels of 0.1 and 0.9). The threshold is set at normalised grey level of 0.5 (50%) in this example. The proportion of edge voxels to bulk voxels, for a given void, will affect the height of the flat portion of the histogram relative to the air peak, as illustrated in Figures 2 and 3.

Whilst this would appear to be logical for total void-volume fraction (V_v) measurements, for pore characterisation of linear sizing (length, width, etc) and morphology, the segmentation method needs to accurately track the pore edges and there are known errors in edge-location when using this 50% threshold for curved edges – see inset diagram in Figure 1. The assumption of the 50% segmentation threshold is that the location of the edge of the pore is at the centre of a voxel with a normalised grey level of 0.5. Errors can occur due to the shape of the pore edge – if it is flat then the error is zero, but any curvature will cause an error in the use of the voxel centre as the pore edge [48].

There are also some cases in which the total V_v is overestimated, due to e.g. scattering noise. This is shown in Figure 4, in which the simulated histogram has wider composite and air peaks due to scattering noise but the same pore size and voxel size as Figure 1. In this case, the 50% threshold will overestimate the pore sizes, on average, and the total V_v, and so the threshold needs to be set at a lower percentage to compensate for this effect. Section 6 will explore methods for automating the setting of this threshold level, based on the histogram.

3. Model description

For this model, the ratio of the measured-to-actual total void volume fraction was chosen as a metric to investigate sources of bias and uncertainty in the characterisation of pore sizes. In each model with spherical pores of a single size, the actual void volume fraction depends on the single pore radius, R and the number of pores per unit volume. Different shapes of pores could be created but, for most of the modelling in this paper, the pores are spheres, so the volume of the pore, V can be obtained using the simple equation for the volume of a sphere.

One pore is created within virtual cube in the data and the ratio of the pore volume to that cube volume is equal to the V_v. The location of the pore within its virtual cube is varied randomly so that, with numerous pores in the model, the relationship between pore-edge locations and voxel centres is randomised and all values of V_v within a voxel are possible, giving a relatively flat but non-zero histogram between the air and composite peaks – see Figure 1. The use of this random pore location avoids a source of systematic errors in the measurements of V_v where certain spikes in the histogram would appear due to specific repeated locations of pore edges within voxels.

The simulated CT data set is generated as a 3D set of voxels, each containing a single scalar value of normalised grey level, based on the following methodology and assumptions:

(a) Grey level is linearly related to effective linear attenuation coefficient:

$$G = a\mu + b \tag{1}$$

where *G* is the CT grey level, μ is the effective linear attenuation coefficient in the voxel, *a* is a contrast, and *b* is brightness.

For this model, a 'normalised grey level' is used, in which 0 corresponds to air and 1 corresponds to composite of the 'nominal' fibre volume fraction.

$$G_{norm} = \frac{\mu - \mu_{air}}{\mu_{composite} - \mu_{air}} \tag{2}$$

The simple volumetric mixture rule has been established as being appropriate for converting the linear attenuation of composite, $\mu_{composite}$ and air, μ_{air} within a voxel into an effective linear attenuation μ:

$$\mu = \phi_V \mu_{air} + (1 - \phi_V)\mu_{composite} \tag{3}$$

where $\mu_{composite}$ is the linear attenuation of the composite, μ_{air} is the linear attenuation of the air and ϕ_v is the void volume fraction V_v.

(b) Voxels at pore edges are divided into sub-voxels for determining grey level. In the model, voxels that are completely within or entirely outside pores have normalised grey levels of 0 or 1, respectively. A voxel at the edge of a pore takes a normalised grey level equal to the proportion of its volume that is outside the pore. This is calculated by dividing the voxel into 1000 sub-voxels (i.e. 10 x 10 x 10). Each sub-voxel is checked to see whether its centre is inside the pore or not, thus determining whether its normalised grey level should correspond to 'air' or 'composite' (0 or 1). The normalised grey level of the voxel is taken as the mean of the 1000 sub-voxel normalised grey levels

(c) In addition, there will be an influence from the X-ray scattering noise during CT-scanning. This is caused by spurious photons arriving at the detector from scattering interactions in voxels other than on the direct X-ray path. To investigate this, randomly-generated normally-distributed incoherent noise (with a mean of zero and a specified standard deviation as a normalised grey-level) is added to the modelled voxel grey levels in the CT data set. Figure 5 shows the effect of scattering noise on the roughness of the 'segmentation-threshold surface' for the spherical voids.

(d) There will be some structural (coherent) noise caused by FVF variations in the composite. This will affect the effective LAC of the voxels in the composite but not in pores, so this normally-distributed noise (with a mean of zero and a specified standard deviation as a normalised grey-level) was only added to the composite voxels where it is effectively combined with the scattering noise in quadrature to give a single normal distribution with a standard deviation equal to the square-root of the sum of the squares of the two (coherent and incoherent) standard deviations.

(e) Resin-only layers between plies and other resin-rich regions exist in composites. Voxels in these resin regions will take the grey level corresponding to the LAC for resin only, plus the added scattering-noise distribution. By default, the resin-only normalised grey level used in the simulator for this paper was set to 0.8, except for the section where the influence of this parameter is explored. If these resin-only regions become an appreciable proportion of the total volume then a third peak in the histogram can appear. This is simulated as actual resin-only layers in the model and a similar volumetric mixture rule issued to determine the grey value for resin-edge voxels.

(f) Finally, a histogram is generated for the whole model as this can easily be analysed to determine the volume above and below a given threshold in order to calculate the 'measured' void volume fraction.

4. Modelling Results and Validation

There are different parameters that can be varied in the model in order to explore their influence on the proposed segmentation methods: (a) sample dimensions; (b) voxel size; (c) resin layer parameters (position and proportion of total volume); (d) void volume fraction, V_v; (e) porosity radius; (f) coherent noise standard deviation due to structural fibre volume fraction (V_f) variations; and (g) incoherent noise standard deviation due to X-ray scattering. However, it is possible to eliminate several parameters that have minimal impact on void measurement. Furthermore, pore radius, void volume fraction (V_v) and number of pores in a sample are inter-related, although they may not all have a significant effect on void measurement.

Figure 6 shows a surface plot of the actual V_v, as a function of pore radius and number of pores in a fixed sample volume of: 0.5 mm^3 with the chosen assessment metric for the parametric study – measured/actual V_v – plotted as a colour on the surface. The model was run on a sample size of 1 mm x 1 mm x 0.5 mm, voxel size of 10 µm, scattering-noise standard deviation (in normalised grey level) of 0.05, using a segmentation threshold of 0.5 (50%). The radius, number and locations of pores were varied between models but all pores within a single model were the same size. Inspection of Figure 6, where each cross symbol indicate the result of a simulation for a given number of pores of a particular size, shows pore radius to have the dominant influence on the measurement bias, i.e. Measured/Actual V_v. This bias is thought to be due to either the lower number of voxels describing the edges of a smaller pore, or the higher curvature of the edges of smaller pores and this is investigated later (in section 4.3).

A simple example of this effect is to consider a 2 x 2 x 2 cube of 8 voxels, containing a pore centred at the cube centre, where the pore volume in each voxel is just less than 50% of the voxel volume. In this case, each voxel will register 1 (not in a pore), the measured pore volume will be zero, but the actual pore volume will be just less than 4 voxels. If the pore is spherical, this corresponds to a pore radius of 0.985 of the voxel size (Eqn. 1). Thus, the 50% threshold will gradually underestimate pore volume as pore radius reduces to 0.985 voxels, at which point the measured pore volume could reduce to zero if the pore is centred on a node between voxels, or anything up to 4 (voxels) if the pore is not at a node. For numerous pores at *random* locations, an average V_v of zero is reached when the pores all have a volume less than 50% of the voxel volume – ie. when the pore radius is less than 0.49 of the voxel size. This effect is demonstrated for *random* pore locations using the simulator in Figure 7.

4.1 Effect of pore-radius to voxel-size ratio.

One of the important parameters governing CT image quality is voxel size, which should be smaller than the structural features that need to be imaged. The minimum achievable voxel size is dictated by two factors: 1) the focal spot size in the source which dictates the geometric unsharpness such that it is pointless reducing the voxel size further; and 2) the ratio of the maximum size of the specimen, or region within a specimen that is to be imaged, perpendicular to the CT rotation axis, to the number of detector pixels across the detector in that direction. For this reason, it can be almost impossible to achieve a voxel size smaller than all the pore sizes in realistic sized test coupons. Therefore, it is important to understand the dependence of V_v measurement on the ratio of pore size to voxel size.

Figure 8 shows the dependence of bias on pore-radius / voxel-size ratio for segmentation thresholds of 40%, 45%, 50%, 55% and the Otsu threshold, which is recalculated for each model and will vary depending on void volume fraction. Statistical variations in the curves were reduced by using a larger total volume of the model but larger models take longer to run so this was a compromise. It can be seen that the 50% threshold and Otsu threshold provide the most accurate segmentation for larger pore sizes (radius greater than 3 voxels). However, none of the thresholds work well with a pore radius less than 4 voxels, at which point the bias is an underestimate of 2% for the 50% threshold and an overestimate of approximately 1% for the Otsu threshold. As in Figure 7, the 50% threshold curve is tending to zero at a pore radius of approximately 0.5 voxels, as predicted by the above analysis for a pore at the centre of 8 voxels.

The 55% threshold gives an exact measurement (zero bias) for one particular pore size. This is where the underestimate due to size or curvature of the pore is exactly cancelled by the general slight overestimate in pore measurements due to the higher threshold. Due to this effect, it has been suggested by Plank et al [40] that the threshold should be increased for larger voxel sizes (lower pore-radius / voxel-size ratio) but real composite contains a distribution of pore sizes, requiring a different threshold for each pore size. A single threshold above 50% may give a more accurate total V_v but the segmentation of void morphology would underestimate the sizes of small pores and overestimate the sizes of large pores.

Figure 9 shows the same data plotted to show the bias in V_v as a function of the segmentation threshold value for selected values of pore radius (in voxels). The slope of each curve is used in the following section for validation of the model against experiment, where total V_v has been measured for a known pore-size distribution.

The conclusion of this study of the accuracy of porosity measurement as a function of pore size is that all small pores will be underestimated in size more than large pores, for any single segmentation threshold. If a threshold above 50% is used, then larger pores could be overestimated in size.

4.2 Model validation

Small samples (230 x 10 x 2.6 mm) with porosity introduced by deliberately adjusting the cure-cycle parameters were manufactured according to the procedure outlined in the authors' previous work [2]. The samples were subsequently scanned using X-ray CT at 55 kV source voltage, 2000 projections, 4 frames per projection, source current 140 mA using a Nikon XTH320 system and Tungsten target material. The data was post-processed within a large volume just inside the edges of the specimen (i.e. excluding air from outside the specimen) using the 50% segmentation threshold. This allowed characterisation of each pore within the samples, in order to determine their morphology, size and location. Quantitative comparisons were made between high-magnification optical microscopy images and the μCT-scans using a 50% segmentation threshold at the same locations within a chosen specimen (as shown in Figure 10). The results showed excellent correlation in terms of the void shape, dimensions, and distribution [2].

To validate the model described above, the CT results of the samples with introduced porosity were analysed to determine the *relative* dependence of total V_v on segmentation threshold to check the slope of this dependence for a known pore-size distribution against a weighted average of the slopes for each size in Figure 8. Firstly, the average void content was calculated from the experimental CT data using different thresholds in the range of 40-60% (Figure 11) within the VG Studio Max software. The voxel size of the CT-scanned sample is 13.1 micron. The 50% threshold determined an average void content of 3.69% with a bias that depends on the threshold (Figure 11), with the non-dimensional slope of the least-squares fitted line equal to 0.0626.

In order to validate the modelling methodology, the experimentally determined slope can be compared with a predicted slope based on a weighted average using the pore-size distribution to determine the weightings. The above analysis and discussion justifies an assumption that the smallest dimension and highest curvature of a given pore will govern the bias in its volume measurement by segmentation. For the investigated material system (IM7/8552), voids tend to be needle-like in shape and elongated in the fibre direction [2]. As a result, the void size in the thickness direction is used for this analysis, as the void size in this dimension will be smallest and therefore will be the dominant contribution to the bias in the V_v measurement and its slope relative to the threshold. Figure 12 shows the experimental thickness-direction void-size distribution of the sample.

The simulator was used to predict the slope of V_v against threshold for the range of pore radii in the pore-size histogram in Figure 12, using a simulated voxel size of 13.1 μm to match the experimental voxel size and a modelled average V_v of 3.7%. Each model uses random void locations but is simplified by creating all voids spherical and of equal size. The results of the analysis are shown in Figure 13, showing that the slopes of the graphs and their absolute V_v differ from the experimental results. This is probably due to the distribution of void sizes in the actual samples where the mean pore size is approximately 50 µm, so the equivalent mean pore *radius* is 25 µm. It is clear from Figure 13 that, as the pore radius reduces below 60 µm (a pore 'size' of 120 µm), the 50% threshold underestimates the total V_v, suggesting that the experimental V_v value may also be an underestimate because the majority of the voids in Figure 12 are smaller than this. Also, it can be seen on Figure 13 that the slope of the graph for a pore radius of 20 µm is 0.059 which is very close to the experimental slope for the full pore distribution. For a pore radius of 25 µm, there is a predicted underestimate in average void content, using a 50% threshold, of about 0.3%. This would suggest that the actual experimental V_v was underestimated by 0.38% and should be approximately 4.08%.

To enable comparison of the modelling and experimental results, a weighted-average slope, ξ, was calculated using the distribution in Figure 12 as the weighting for each bar of the graph using a pore size at the middle of the bar:

$$\xi = \sum_{i=1}^{N} w_i \xi_i \Big/ \sum_{i=1}^{N} w_i \tag{4}$$

where N is number of analysed bars in the graph in Figure 12, w_i is the number of pores in the range of sizes represented by bar i in Figure 12, ξ_i is the gradient of void volume fraction vs threshold for a pore radius corresponding to the middle of bar i in Figure 12. The model-predicted weighted-average slope is 0.0552, which is 12% less than the experimental value of 0.0626. This provides an acceptable agreement between model and experiments considering the experimental pore shapes are not spherical and it is difficult to know which dimension of pore size to use for the comparison.

A similar calculation for the underestimation by the 50% threshold gave a weighted-average underestimate of 0.45%, suggesting that the true V_v of the experimental sample is 4.15%.

4.3 Effect of the pore-edge curvature

It is not obvious whether the underestimation of pore size for small pores is just due to the size itself (i.e. the ratio of edge to bulk voxels) or also to do with the increased curvature of the edges due to the effect shown in Figure 14.

In order to investigate the effect of edge curvature on pore segmentation, spherical and cubic pores were compared (See Figure 15). Although cubes have a large amount of surface with no curvature, they do of course have a very high curvature at edges and corners, so this is not a perfect test.

The resulting effect is illustrated in Figure16, in which it is shown that at smaller pore radius/voxel sizes the error using spherical pores is larger than for the cubic pores. The conclusion is that there is a curvature effect working in combination with the pore-size vs voxel-size effect discussed above.

Although the cubic pore edges were parallel to the voxel edges in these simulations, this has not biased the result because it does not matter at what angle the flat pore surface cuts through a voxel. If a flat plane passes through the centre of the voxel, at any angle, the voxel will be bisected, so 50% of the voxel volume is either side of the plane. Thus, the voxel centre correctly identifies the location of the pore surface. The effect demonstrated here is purely explained by the fact that a *curved* surface with 50% of the voxel volume on each side, will *not* pass through the voxel centre and the voxel centre falls just inside the pore, causing an underestimation of its size (Figure 14).

5. Parametric study of segmentation thresholds

5.1 Effect of the (incoherent) scattering noise

Scattering noise is one of the most common CT artefacts, and can affect the segmentation boundary of the pores on the CT-images. It is possible to reduce it by increasing the number of images (shots) per projection and averaging them, or by applying the noise filter in the reconstruction software, if provided. Scattering noise will affect the measured grey value of each voxel. It is assumed that, in the histogram of grey levels, the scattering noise manifests itself as a normal distribution around the mean grey value for the relevant material. In the simulator, the scattering noise is added by specifying a standard deviation for that normal distribution but the mean value of the distribution for that material is not affected.

From experience, for optimised CT-scanning, an acceptable normalised grey-level scattering noise is between 0.1 and 0.15. Figure 17 shows the grey-level histogram of the experimental CT-scan of the porosity sample. Scattering noise standard deviation calculated from the experimental histogram is 0.11.

Both the 50% and Otsu thresholds show increasing over-estimation of void volume fraction with increasing scattering noise (Figure 18). In addition, the behaviour is erratic and bias is high for the Otsu threshold with a scattering-noise standard deviation above 0.15. For the 50% threshold, a maximum bias of 18% occurred at a pore radius of 10 voxels and scattering noise of 0.2, but the behaviour of the 50% threshold is more stable than the Otsu threshold for all levels of scattering noise.

Two-dimensional slices through the simulated CT datasets, illustrating the effect of three scattering-noise levels (0.05, 0.15, 0.2) on the pore imaging, are shown in Figure 19 for two selected pore radii of 1 and 5 times the voxel size.

5.2 Effect of (coherent) structural noise

Additional noise can contribute to the 'composite' peak distribution due to fibre volume fraction, V_f, changes because fibres and resin have different LAC values. The normalised grey level takes a value of unity for the LAC of a 'nominal' V_f and the default resin-only normalised grey level used in this paper is 0.8, although this is varied later in a study of this parameter. Note that a nominal V_f of 60% was used in the simulator for the composite regions. Thus, a standard deviation in V_f of 10%, which would be a large manufacturing deviation, corresponds to a standard deviation in normalised grey level of 0.033.

From Figure 20, it can be seen that both of the compared thresholds (i.e. 50% and Otsu) perform well, with bias of less than 5%, even with a large standard deviation (10%) in the V_f, above a pore radius of twice the voxel size.

5.3 Effect of the resin-layer parameters.

5.3.1 Grey level of resin vs composite

The grey-level histogram of a composite-material CT-scan usually comprises three peaks that correspond to 'air, 'resin' and 'composite', in order of increasing effective LAC. The LAC of a material is based on the chemical formula, which defines its effective atomic number [50] and its electron density. Therefore, by changing a composite's material constituents (e.g. resin or fibre materials), or by changing the nominal fibre volume fraction, the normalised grey level of the resin peak may vary significantly. For the purposes of this parametric study, it has been allowed to vary from 0.6 to 0.9 in the normalised grey-value histogram (Figure 21). In some composites, such as most carbon/epoxy composites, the 'resin' and composite' peaks will be merged due to similarities in their LAC. However, when the resin's normalised grey level is low and/or the scattering noise is high, there is a chance that the lower tail of the resin peak will cross the 50% threshold, causing resin voxels to be counted as air and resulting in an overestimate in porosity V_v as shown in Figure 21.

Figure 22 and Figure 23 show the effect of varying the resin-only normalised grey level, as a function of scattering noise, on porosity segmentation. A fibre volume fraction (V_f) standard deviation of 10%, equivalent to a normalised grey level of 0.033, is used as discussed previously, and the proportion of resin layer to total volume is chosen as 0.1 as this corresponds to an average of widely used composite material systems.

Both of the thresholds (as shown in Figure 22 and Figure 23) show significant sensitivity to both the resin-only grey level and the scattering noise, both of which can act to increase the voxels that masquerade as pores, to the left of the threshold. In fact, the Otsu threshold failed to perform at a resin-only normalised grey value of 0.6 for any noise level (see Figure 23), whilst the 50% threshold functioned well at a resin normalised grey value of 0.6 for scattering noise levels below 0.05. Both thresholds performed well (bias less than 5%) for scattering-noise standard deviations below 0.15 (around the largest normally seen) at a resin-only normalised grey level of 0.8 (relative to composite at 1 and air at 0), as used in the rest of this paper as a default.

5.3.2 Thickness of the resin layers

Another potentially significant parameter is the thickness of the inter-ply resin layer as a proportion of the ply spacing, as this will change the height of the resin peak in the histogram relative to the composite peak and a higher resin peak will have more voxels masquerading as pore voxels to the left of the threshold. The resin-layer thickness may vary for different types of fibre-resin systems, particularly with particle-toughened resin layers, which tend to be thicker – up to 25% of the ply spacing. This variation in the relative height of the resin peak may affect porosity measurement during CT-image segmentation if the resin peak overlaps the 50% threshold.

The results in Figure 24a show a high sensitivity of both thresholds to resin-layer thickness at a resin grey value of 0.6. More acceptable behaviour can be seen for the resin grey value of 0.8, providing a maximum error of less than 1% and 2.5 % for Otsu (Figure 24b) and 50% threshold respectively.

6. An adaptive threshold

The 50% threshold shows very good results for void measurement in most cases but does not perform well in situations where the resin peak encroaches upon the 50% threshold because either the histogram has three distinctive peaks or the noise level (scattering and/or structural) is high. In these cases, the threshold needs to be reduced below 50%, otherwise it will overestimate the void fraction and the segmentation of each void will incorrectly determine void size. The problem is how to determine what threshold will minimise the error. As explained above, the crucial factors are how much the lower part of the resin peak overlaps the 50% threshold and how much of the histogram in that overlap is genuinely air. This overlap is characterised by two parameters – the relative height of the overlap and its positive slope.

The adaptive algorithm that is proposed to determine the appropriate threshold (Figure 25), or the 50% threshold if this is appropriate, involves the following steps:

- The grey-level histogram should be smoothed to remove local minima due to noise, using a moving average, the width of which depends on the noise structure of the histogram (as opposed to the scattering noise in the CT scan which just spreads the peaks).
- The air peak, ($g_{\mathrm{air}}, f_{\mathrm{air}}$), is determined from the smoothed histogram where g is the grey level and f is the frequency of voxels in the histogram at that grey level.
- The first minimum, ($g_{\mathrm{min}}, f_{\mathrm{min}}$) above g_{air} is identified.
- if $f_{min} > f_{air}/2$, the first minimum (g_{min}, f_{min}) is taken as the grey-level threshold (Figure 25a.)
- if $f_{min} < f_{air}/2$, the next crossing of $f_{air}/2$ is taken as the grey-level threshold (Figure 25b), or 50% (Figure 25c), whichever is lowest.

Figure 26 shows the effect of the resin-peak overlap, varied by changing the scattering-noise standard deviation, on void segmentation using both the 50% and proposed adaptive thresholds. The new adaptive threshold is equivalent to the 50% threshold up to a scattering noise level of 0.125. An increase of the scattering noise beyond this level causes the error of the 50% threshold to increase and deviate from the proposed threshold. As a result, once the resin histogram overlaps the grey value of 0.5 (indicated in this case by a scattering noise level greater than 0.1 for resin grey values of 0.6 and 0.7 and a scattering noise level of 0.125 for resin grey values of 0.8 and 0.9), estimation of the void volume fraction is improved by adopting the new adaptive threshold. The maximum error in V_v with the proposed adaptive threshold is less than 10%, whilst the 50% threshold shows significantly higher errors.

Figure 27 adjusts the amount of overlap of the 50% threshold by changing the resin-layer thickness, and thus the proportion of resin by volume. In comparison with the 50% threshold, the adaptive threshold works very well with thick resin layers. Its application reduces the maximum error to 3.5%. There is no observed detrimental effect from using the adaptive threshold for any of the tested ranges of noise level, resin grey level or resin-layer thickness.

Figure 26 and Figure 27 show the effectiveness of the adaptive threshold in cases of higher scattering noise and lower resin grey values. Whilst these graphs were produced using an average void content of 10%, it is recognised that industry typically has a porosity acceptance criterion of less than 2%. Figure 28 shows that for the more typical lower porosity levels - from 0.5% to 2% - the adaptive threshold still performs much better than the 50% threshold, having a smaller underestimate of the true value of the average void content than the 50% threshold overestimates.

7. Conclusions

Using X-ray computed tomography alongside simple and accurate image segmentation methods allows the detection and measurement of critical void defects (i.e. the void location, shape, and size). This information is essential for the understanding and assessment of the effect of defects on the composite structural performance. However, until now there has been a lack of understanding of the systematic effects of the choice of segmentation threshold level when characterising porosity. This paper has used a simple model to simulate the CT response to porosity in order to be certain of the 'true' value of void volume fraction, allowing a full parametric study to be performed.

A common CT-segmentation thresholding method (50% threshold), based on the assumption that a voxel should count as a pore-voxel if more than half of its volume is air, otherwise it is not counted as a pore, has been shown to be more accurate than other methods in all but a few situations. The accuracy of this 50% threshold method has been demonstrated for a range of properties: material (resin-layer grey level and thickness), porosity (pore radius and void volume fraction) and CT (scattering noise and voxel size). Smaller pores relative to the voxel size are underestimated in size by this method (as by most thresholds) due to the curvature of the pore edge. However, there is potential for using the modelling results to apply a correction for V_v based on the distribution of pore sizes and the simulated underestimate of V_v as a function of pore size. Noise, either scattering (incoherent) or structural (coherent), causes overestimation of pore sizes, particularly when the resin attenuation is low compared with the composite, such as with glass fibre reinforced polymers.

The application of the 50% threshold on unidirectional carbon/epoxy samples, containing porosity, demonstrated excellent correlation to the microscopic measurements, both qualitatively and quantitatively. Comparison of the 50% threshold to the other thresholds showed the 50% threshold performed better in most cases, such as with composites that have thin resin layers, carbon/epoxy composites with a resin peak grey level of approximately 0.8, and for images with low-to-medium scattering noise.

In some situations, for instance in the presence of a high level of scattering noise and/or a low grey value of the resin peak, the threshold needs to be set to a lower value to reduce the overestimation of porosity due to some resin voxels masquerading as pores because they are below the 50% threshold. To address this issue, a new adaptive algorithm has been proposed to find an appropriate threshold. This algorithm has been demonstrated using simulations to have significantly improved porosity measurement capabilities and reduced bias in the measurements for void volume fractions from 10% down to 0.5%.

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